Chapter 3. Value-Lost: The Hidden Cost of Teacher Misassignment

List of names

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Abstract (142 word)

Extensive evidence suggests that students are negatively impacted when taught out-of-field, but most of the extant literature is based on (a) national or international exam scores where the exams are not aligned directly with the course curriculum being taught, or (b) self-reported survey data. This study used state-wide, detailed data for 5 million students who took Algebra I, Grade 8 Mathematics, or Grade 7 Mathematics and their associated state-level exams, detailed rules for who is teaching in-field versus out-of-field, and rigorous value-added modelling that consists of three-level, mixed effects hierarchical models. The results are unequivocal: students earn significantly and substantially lower exam scores when taught out-of-field compared to peers taught in-field. Students taught out-of-field are experiencing "value lost," not "value add," relative to their peers taught in-field. The federal and state policy implications for teacher misassignment are explored, and recommendations made.

Keywords teaching out-of-field, quantitative methods, value-added modeling, student academic growth, educational equity

Citation:
Van Overschelde, J. P. (in press). Value lost: The hidden costs of teacher misassignment. In L. Hobbs & G. Törner (Eds.), *Out-of-Field Teaching Across the Teaching Disciplines and Contexts*. Dordrecht: Springer.

1. Introduction

Research shows that students suffer academically when they take a class that is taught by a teacher without the requisite qualifications to teach the class (Clotfelter, Ladd, & Vigdor, 2010; Dee & Cohodes, 2008; Goldhaber & Brewer, 2000; Raudenbush, Fotiu, & Cheong, 1999; Riordan, 2009). Unfortunately, almost every rigorous, quantitative study to date has used outcomes based on national or international assessments (e.g., National Assessment of Educational Progress [NAEP], Trends in International Mathematics and Science Study [TIMSS]) that are not necessarily aligned with the curriculum the teachers taught in the class. Only one large-scale study exists that used detailed student and teacher data where the assessment data was linked to the class being taught (Clotfelter et al., 2010). Unfortunately, the study compared student academic growth for students of teachers who held subject-specific teaching licenses against those who held no teaching license.

The lack of outcome measures that are directly aligned with the curriculum being taught leaves a clear gap in the extant literature – is teaching out-of-field harmful for students' academic growth when the assessment is directly aligned with the curriculum? As Porsch and Whannell (2019) recently argued, the field needs "a more sophisticated approach to defining out-of-field… and methodological techniques such as multilevel regression modeling on an appropriately sized dataset" (pg. 179). The present study meets this call. This study involves a more sophisticated approach to defining out-of-field (i.e., state law) and involves multilevel, hierarchical linear modeling with data on millions of students to start filling this hole in the extant literature.

Teaching out-of-field was essentially illegal in the United States between 2001 and 2015. In 2001, the United States Congress passed the federal law *No Child Left Behind Act of 2001* (NCLB) after which public schools in the US were required to assign teachers to classes only if the teacher held full state teaching certification and possessed solid content knowledge of the class's subject. These so called *highly qualified* teachers were teaching within their field of expertise or teaching in-field. Highly qualified teachers in middle or secondary grade levels had to hold a bachelor's degree or higher degree and pass rigorous subject-specific licensure tests in each academic subject the teacher taught (NCLB, Sec. 9101[23]). As of 2002, every new teacher hired had to be highly qualified, and by 2005-06 all teachers in core academic subjects had to meet this standard. NCLB prescribed a limited number of conditions in which a principal could assign a teacher to teach a core subject out-of-field, and parents of students in these classes were required to be notified when a class was taught out-of-field. In response to this federal mandate, states developed specific rules to operationalize these mandates within each state's educational context.

In Texas, the state education agency that oversees P-12 public schools and teachers operationalized the state's teacher licensure system by codifying the teaching licenses required to teach each course subject. Texas Administrative Code (TAC §231) contains 82 pages of licensure rules by subject area and grade level. For example, to teach Chemistry in Grade 9 in-field, a teacher must hold a teaching license in either Chemistry, Science, Physical Science, or Math/Physical Science/Engineering for a grade band (e.g., 7-12) that includes Grade 9. A teacher who holds a Physics, Biology, or English license would not be certified to teach Chemistry and would be teaching Chemistry out-of-field.

This detailed licensure map is important because Texas teachers can hold multiple teaching licenses. The initial license is generally awarded after the person completes a teacher preparation program and passes a subject-specific, grade banded content test and a pedagogical test. After this first teaching certification or license is awarded by the state, a teacher can train for and take additional licensure tests to demonstrate their expertise in dozens of other content areas and/or grade levels. For example, a teacher prepared and certified to teach Chemistry in Grades 7-12 could study Physics education and pass a Physics licensure test to earn a Physics teaching license in Grades 7-12. Or, a teacher certified to teach Mathematics in Grades 7-12 can learn the Math content and requirements for middle grades and take a licensure test to teach Mathematics in Grades 4-8. Additional academic degrees are not required to gain additional licenses; expertise is demonstrated by passing a content-specific licensure test. This decision to allow multiple licenses without relying on additional degrees or additional higher education enrollment is supported by research that shows teaching courses within a secondary certification field results in similar levels of student academic achievement as teaching courses within the primary certification field (Sheppard, Padwa, Kelly, & Krakehl, 2020).

In 2015, the United States Congress passed the *Every Student Succeeds Act* (ESSA) to replace NCLB. ESSA removed the highly qualified teaching requirement in order to give states and school district more local control. Now, federal laws essentially permit schools to assign any teacher to any class regardless of the teacher's qualifications or expertise for the subject area or grade level being taught. In other words, ESSA legalized teaching out-of-field. However, ESSA does require different student groups to be treated equitably. In other words, it is acceptable under ESSA to assign teachers to teach out-of-field as long as White students, Black students, and Latinx students (for just some examples) are equitably assigned to out-of-field classes (ESSA, Sec. 1111[g][1][B]). States are required to report to the federal government plans that ensure low-income students and students of color "are not served at disproportionate rates by ineffective, out-of-field, or inexperienced teachers" (Sec. 1111).

Van Overschelde and Piatt (2020) showed this equitable assignment is clearly not happening. They found that Black students, male students, students from low-income families, students in communities other than urban and suburban, and many other groups are significantly more likely to take classes that are taught out-of-field – relative to their White or Latinx, female, and wealthier peers. To determine whether this inequitable assignment of students to out-of-field classes is inequitably impacting students' academic growth, detailed student-teacher-course-assessment-licensure data for millions of students and tens of thousands of teachers from Texas were used.

The overarching question being examined are: Is teaching out-of-field bad for students academically when the material being tested is directly aligned with the material being taught? Are the federal ESSA mandates for student equity effective at ensuring an equitable education for all students?

2. Literature Review

When "teachers [are] assigned to teach subjects for which they have inadequate training and qualifications" (Ingersoll, 2019, p. 21), they are teaching out-of-field. Out-of-field is a characteristic of a class-teacher pairing or a description of the misalignment of the teacher's qualifications with the class taught (Sanders, Borko, & Lockard, 1993). Ingersoll (1999) captured this misassignment issue succinctly with an analogy. Ingersoll said that assigning a teacher to teach out-of-field is equivalent to requiring "cardiologists to deliver babies, real estate lawyers to defend criminal cases, chemical engineers to design bridges, or sociology professors to teach English" (pg. 34). A doctor licensed in cardiology but practicing obstetrics is not an unqualified doctor, but unqualified to deliver babies. Similarly, a teacher certified to teach English but teaching Algebra I is not an unqualified teacher, but unqualified to teach Algebra I.

Therefore, a class is taught out-of-field or a teacher is assigned to teach a class out-of-field, but a teacher is not an out-of-field teacher. It is also true that a teacher can teach some classes in-field and other classes out-of-field in the same school year (Hashweh, 1987). Unpublished data from my lab show teachers can teach anywhere from 0% of their classes out-of-field to 100%, with every combination in between.

In the USA, research shows this misalignment of teacher and class is largely the result of decisions made by the school principal (Carey & Farris, 1994; Ingersoll, 1993; Ingersoll, 2002; Ingersoll, 2019). Ingersoll (2019; see also Ingersoll, 2002) argues that the misassignment is not due to a general lack of certified teachers, but more to an idiosyncratic lack of certified teachers willing to take a particular job at a particular school for the proffered salary. This makes intuitive sense. Imagine trying to convince a teacher certified to teach Algebra II to move from their current urban or suburban locale to a rural locale where they know no one, usually with a concomitant lower salary. Principals are also operating within a limited budget so that, for example, when student enrollment results in one unstaffed English class, the principal must decide among a limited set of options: hire a certified teacher to cover that one class, hire a less-qualified substitute teacher, reassign a non-English teacher who has an open period, or redistribute the students from the unassigned class to the assigned English classes (and disrupt the master school schedule).

Educational Equity

Why should we care about teaching out-of-field? First and foremost, teaching out-of-field is bad for students for many reasons. To summarize, students taught out-of-field appear to experience less academic growth and lower academic performance because teachers teaching out-of-field generally engage in less effective instructional practices (e.g., scaffolding, question asking, content elaboration, lower pedagogical content knowledge) and are less able to create classroom environments that are conducive to student learning and academic growth.

Student Academic Growth

Students taught in out-of-field classes experience less academic growth and lower academic performance than students taught in-field (Chaney, 1995; Clotfelter, Ladd, & Vigdor, 2010; Dee & Cohodes, 2008; Goldhaber & Brewer, 2000; Ingersoll, Perda, & May, forthcoming, as cited in Ingersoll, 2019; Raudenbush, Fotiu, & Cheong, 1999; Riordan, 2009; Tsai & Young, 2015) because teachers cannot engage in more effective instructional practices (Blazar & Kraft, 2017; du Plessis, 2015, 2016; Hobbs, 2013; Pianta & Hamre, 2009).

Clotfelter et al. (2010) conducted one of the most rigorous quantitative studies to date to explore student achievement differences between students taught in-field and students taught by a person with no teaching license. Using rich, panel data from North Carolina, they computed value-added growth scores for high school students using scores from the state's end-of-course exams. Aggregating results across multiple subject areas, they found that students experienced significantly higher academic growth when classes were taught in-field compared to when classes were taught by an unlicensed person, after controlling for a host of other variables. The magnitude of the relationship between teaching in-field (versus an unlicensed person) and student academic growth was stronger than the competitiveness of the teacher's undergraduate university, the years of teaching experience, whether the teacher held a graduate degree, the teacher's scores on the state licensure exams, and even holding National Board Certification.

Using a subset of student data from New York, Sheppard et al. (2020) found that aggregated school-level performance on the state's chemistry and physics exams was higher in schools where more students were taught in-field compared to schools where more students were taught out-of-field, and performance was similar across initial certification field and secondary certification fields (i.e., certification by exam). These analyses were based on school-level performance therefore student-level academic growth could not be evaluated directly.

Using national test data or small sets of survey data, similar patterns of results have been obtained. For example, Ingersoll et al. (forthcoming, as cited in Ingersoll, 2019) analyzed National Assessment of Educational Progress (NAEP) scores for Geography, History, Math, Reading, and Science and found significantly higher test scores on all tests when students were taught in-field compared to students taught out-of-field. Dee and Cohodes (2008) examined the National Education Longitudinal Study of 1988 (NELS) dataset and found students in Grade 8 experienced higher test scores in Math and Social Studies when taught in-field, but no difference for English and Science. Using the NELS dataset, others have found positive benefits of in-field teaching for Math and Science in secondary grades (Goldhaber & Brewer, 1997, 2000; Monk & King, 1994). The consistency of these findings is intriguing because the tests of academic achievement on which these studies were based were not necessarily aligned with the curriculum being taught in the year the tests were administered.

The negative relationship between academic achievement and out-of-field teaching has also been observed with younger students too. Riordan (2009) analyzed data for students enrolled in kindergarten through Grade 3 and found higher achievements in Math and Reading for students in classes taught in-field compared to out-of-field.

None of these studies is definitive in and of itself. However, collectively they do suggest a negative relationship between teaching out-of-field and student learning.

Student Enrollment

This finding that taking classes taught out-of-field hurts student learning is important because extensive evidence indicates that students are not equitably enrolled in out-of-field classes. Students from low-income families are more likely to take out-of-field classes than students from wealthier families, students of color are more likely to take classes out-of-field than White students, and students in rural communities are more likely to classes out-of-field than students in suburban communities (Ingersoll, 2008; Ingersoll & Gruber, 1996; Jerald & Ingersoll, 2002; Lankford, Loeb, & Wyckoff, 2002; Nixon et al., 2017; Seastrom et al., 2004; Van Overschelde & Piatt, 2020). This pattern of results obtains despite the fact that Ingersoll used self-reported survey data from the US Department of Education's School and Staffing Survey (SASS), Lankford et al. (2002) used statewide New York enrollment data, and Nixon et al. (2017) used a small samples of teachers from across several states. The most recent study of student enrollment in classes taught out-of-field was conducted by Van Overschelde and Piatt (2020) who examined detailed student data from Texas to examine student enrollment in out-of-field classes. They showed that Black students, male students, students from low-income families, student classified as English-language learners, and students receiving special education services took significantly more classes out-of-field than their peers.

3. Methodology

This study was conducted to address many of the data limitations that have existed in prior studies on out-of-field teaching and to explore the relationship between out-of-field teaching and student academic outcomes using rich data and a rigorous multilevel mixed-effects methodology. The research questions explored are:

1. Do students who are taught Algebra I in-field versus out-of-field experience similar levels of academic growth, after accounting for differences among students, teachers, and schools?

2. Do students who are taught Grade 8 Mathematics in-field versus out-of-field experience similar levels of academic growth, after accounting for differences among students, teachers, and schools?
3. Do students who are taught Grade 7 Mathematics in-field versus out-of-field experience similar levels of academic growth, after accounting for differences among students, teachers, and schools?

Data sources

Texas is an ideal location for conducting research on teaching out-of-field because of the rich data collected by the state's education agency and because it is the second largest state in the USA from the perspective of student enrollment in public education. Specifically, in 2019-20, 5.5 million students were enrolled in 8,900 Texas public schools and these schools employed 363,000 teachers. Since 1991, all Texas public schools have been required to send detailed information about their students to the state. These student data include, for examples, enrollment and demographics, courses taken and grades earned, educational services received (e.g., special education, gifted-talented, English language), standardized assessment scores, attendance, and discipline issues. The schools are also required to report detailed information on their teachers including courses taught (e.g., subject, grade level, days and times the classes meet), academic degrees held, salary, other non-classroom assignments (e.g., instructional mentor, assistant principal). The state also collects teaching licenses held and licensure test performance.

In 2007, the Texas Legislature authorized the creation of the largest research-only state longitudinal data system in the USA. Three Education Research Center (ERC) exist and each houses a copy of much of the state's education data as well as employment data collected by the state's workforce agency (described in detail below). To protect the confidentiality of individuals, personally identifiable data (e.g., names, date of birth) are removed so no individual person can be identified. However, to facilitate research studies and evaluations, each person is assigned two unique IDs to enable each person to be longitudinally tracked across decades. Theoretically, a person can be tracked from entry into elementary school through retirement if the person lived exclusively in Texas. The ERC data can be accessed only after receiving authorization from the ERC Advisory Board and only through secure research facilities from within one of the three higher education institutions in Texas that houses an ERC. To conduct the studies described here, I received permission from the ERC Advisory Board to access the confidential data through the University of Houston's ERC.

Data preparation

Determining whether the millions of students taught by tens of thousands of teachers were taught in-field versus out-of-field required extensive data preparation.

I start with an overview of the preparation process before providing the details. Summary: Every student who completed Algebra I, Grade 8 Mathematics, and Grade 7 Mathematics between the fall of 2012 and the summer of 2019 was selected from the state's master dataset and the teacher of record was identified (when known). I then determined whether each teacher held the state-required teaching license to teach the course.

The details follow. The state's master dataset contains a list of every unique combination of student, school year, school, course, course sequence (e.g., fall, spring), and service code (i.e., subject taught). Hereafter, the term *course* will be used as a shorthand to indicate a unique *school year-school-course-sequence-service* record. The master *Student-Course* dataset for secondary students contains almost 235 million records. From this master dataset, only records for Algebra I, Grade 8 Mathematics, and Grade 7 Mathematics were selected; this resulted in 14.6 million course records. Student demographic data including gender, ethnicity, economic disadvantaged status, English language learner status, and special education status were added.

The teacher or teachers of record for each course was identified if that information was reported to the state. Only courses with a single teacher were retained; this reduced the sample to 13.2 million records.

Out-of-field was determined at the student-course level by comparing all valid teaching licenses held by the teacher of record against each student's grade-level, the course being taught, and the state's licensure requirements for teaching that course. Current state educator licenses are valid for either one year (probationary/emergency) or five years (standard), and older licenses were issued for the educator's lifetime. Therefore, a license was considered valid if the effective date of the license was before the teacher's assignment start date for the course. Years of teaching experience and academic degree held at the time the course was taught were then added.

The outcome measure used for RQ1 was the normalized (z-score transformed) score for the state's Algebra I end-of-course (EOC) exam, for RQ2 was the normalized score for the state's Grade 8 Mathematics exam, and for RQ3 was the normalized score for the state's Grade 7 Mathematics exam. The Algebra I exam is administered to students who enrolled in Algebra I and it is a high stakes exam; students must pass the exam to graduate from high school. As a result of the graduation requirement, students are permitted to take the exam multiple times. Only the first attempt at the EOC was used. The Grade 7 and 8 Mathematics exams are taken during the spring semester of that school year. Grade 8 Mathematics is higher stakes than Grade 7 because students are "required" to pass the Grade 8 Mathematics exam to be promoted to Grade 9. Three attempts at the Grade 8 exam are offered, and the only the first attempt was included here.

The student's prior year's normalized Mathematics exam score was used in several analyses as a pretest covariate. As Algebra I can be taken in different grades, only students who took it in Grades 8 or 9 were examined because 93% of Algebra I students took the course in one of those two grades. For students who took Algebra

I in Grade 8, the Grade 7 Mathematics exam was the pretest used and for students who took it in Grade 9, the Grade 8 Mathematics exam was the pretest used.

Finally, because multiple course records can exist for a student during a school year (e.g., fall and spring semesters), only the last record for the spring semester were retained. This last step reduced the size of the final dataset to 5 million unique students who took either Algebra I, Grade 8 Mathematics, or Grade 7 Mathematics between spring 2013 and spring 2019, who were taught by a single teacher, who had complete demographic and prior math performance data, and who were taught by teachers who had complete data.

The demographic information for students in each of the final datasets is show in Table 1. The Algebra I sample included almost 1.8 million students taught by 20,554 teachers employed by 3,820 schools. The Grade 8 Mathematics sample included over 1.4 million students taught by 14,971 teachers employed by 2,495 schools, and the Grade 7 Mathematics sample included just under 1.8 million students taught by 16,966 teachers employed by 2,556 schools.

Analytic design

Three different sets of three-level, hierarchical, mixed effects regression models were estimated with students at Level 1, teachers at Level 2, and schools at Level 3, with each aligned to a corresponding research question. The datasets were constructed so that the lower-level units were strictly nested within the next higher-level units. Stata v16.1 *mixed* procedure was used. Given the large number of clusters, full maximum likelihood estimation was justified (Snijders & Bosker, 2012). The sample size was more than sufficient for producing unbiased regression coefficients and variance components (Lee & Hong, 2021). Covariance structure of the random effects was treated as independent. The outcome measures were screened for outliers. The extreme values at both ends of the distribution of the test scores were earned by hundreds of students and were, therefore, treated as not outliers. All dummy codes were coded as 1 = Yes.

Unconditional (null) models without any predictors were estimated for each outcome variable to test for systematic within- and between-teacher and -school variance in outcome scores (Raudenbush & Bryk, 2002). Intraclass correlations (ICC) were then computed, one for each of the three outcome measures by dividing the variance at each level by the sum of the variances at all three levels.

For Model 1, student-level predictors known to be correlated with student enrollment in classes taught out-of-field (Van Overschelde & Piatt, 2020). These variables included normalized prior year's Math score, Female status, ethnicity dummy codes for Asian, Black, Other, and White with Latinx as the largest and excluded reference group, and dummy codes for economically disadvantage status, English language learner status, and special education status. Also included were dummy codes for the different school years with 2012-13 as the excluded reference group. Because the test used for the prior score would vary substantially between students who took Algebra I in Grade 9 (Grade 8 Mathematics is the prior) and students who took Algebra I in Grade 8 (Grade 7 Mathematics is the prior), a Grade 9 variable was also added. The variable had a value of 1 if Algebra I was taken in Grade 9 and 0 if it was taken in Grade 8.

For Model 2, teacher-level, fixed- and random-effect predictors were added. The random-effect variable was a dummy code indicating whether the teacher was teaching the course out-of-field. The teaching out-of-field variable was treated as random after all three likelihood-ratio tests showed these models significantly improved model quality compared to the models with teaching out-of-field treated as a fixed effect. The fixed-effect variables were teaching experience and dummy codes for the academic degree held with the bachelor's degree as the largest and excluded reference group.

For Model 3, school-level fixed-effect dummy codes for the school's locale (e.g., urban, suburban, rural; see Texas Education Agency, 2019) were added with Suburban as the largest and excluded reference group.

4. Findings

A basic summary of the findings is: students who were taught out-of-field experience significantly and substantially less academic growth in Algebra I, Grade 8 Mathematics, and Grade 7 Mathematics then their peers who were taught in-field after accounting for important differences among students, teachers, and schools. The student taught out-of-field are losing ground academically relative to their peers taught in-field. The details of the different models are described next.

For Algebra I, the ICC indicates that 40.6% of the variance in scores was at the school level (among schools), 11.3% was at the teacher level (among teachers within a school), and the remaining 48.1% was at the student level (among students within a teacher's classrooms). The variance at all three levels was significant. For Grade 8 Mathematics, the ICC indicates that 12.5% of the variance in scores was at the school level, 18.7% was at the teacher level, and the remaining 68.8% was at the student level. For Grade 7 Mathematics, the ICC indicates that 12.5% of the variance in scores was at the school level, 19.8% was at the teacher level, and the remaining 67.7% was at the student level. These results indicate the necessity for using a multilevel statistical modeling approach to answer all three research questions (Snijders & Bosker, 2012). The large amount of school-level variance for Algebra I and the substantially smaller amount of school-level variance for the other two outcomes is interesting and may reflect the fact that students who take Algebra I in Grade 8 are often in different schools (e.g., middle grade schools) compared to students who take Algebra I in Grade 9 (e.g., high schools). This explanation is explored analytically below.

Algebra I

The modeling results for Algebra I are shown in Table 2. First, every student-level variable in Model 1 was significant thereby supporting their inclusion in subsequent models. The likelihood-ratio (LR) test indicates a significant improvement in the model fit between the unconditional model and Model 1 ($\chi^2 = 971733.0$, $p < 0.0001$).

The differences in variance components across the two models are dramatic. The null model shows that 39.7% of the variance in test scores was at the school-level, that is among schools, and Model 1 showed only 4.4% of the variance remained at the school-level after adding the student-level fixed effect variables. The percentage of variance explained (PVE) was computed by computing the difference between the school-level variance of Model 1 and the null model and dividing the difference by the school-level variance of the null model. The PVE was 88.9%; this is the percentage of school-level variance explained by adding the student-level fixed effects. To determine the degree to which the PVE result was due solely to Grade 8 students being enrolled in different schools from Grade 9 students, Model 1 was rerun without the Grade9 variable. The LR test result shows that including the Grade9 variable substantially improves model fit over the model without it ($\chi^2 = 1187.7$, $p < 0.0001$), but the difference in PVE between the null model and Model 1 with versus without Grade9 showed a 5.9 percentage point difference. The vast majority of the variance explained in Model 1 came from student demographic characteristics thereby strongly implying systematic sorting of students to schools with higher scoring students enrolling in different schools than lower scoring students.

Research Question 1 asks whether students taught Algebra I out-of-field experience similar levels of academic growth as students taught in-field, as reflected in their Algebra I EOC exam scores and controlling for their Mathematics performance the prior year. The results for Model 2, which included all of the variables in Model 1 plus a random-effect variable for teaching out-of-field and teacher-level fixed effect variables for teaching experience and academic degree held, show that teaching out-of-field reduces student academic growth in Algebra I significantly ($Z = -17.61$, $p < 0.0001$), with test scores reduced by 11.1% of a standard deviation after accounting for the student-level variables. The LR test indicates a significant improvement in model fit between Model 1 and Model 2 ($\chi^2 = 1264.9$, $p < 0.0001$). After accounting for the student- and teacher-level variables, only 3.7% of the variance is left at the teacher level.

The results of Model 3, which included Model 2's variables plus dummy codes for each school's locale (e.g., urban, suburban, rural), shows that teaching out-of-field was still highly significant ($Z = -16.40$, $p < 0.0001$) with teaching out-of-field associated with a reduction in scores equivalent to 10.4% of a standard deviation. LR test shows Model 3 resulted in a significant improvement in model fit over Model 2 ($\chi^2 = 126.5$, $p < 0.0001$). The PVE result for school-level variance comparing Model 2 and Model 3 shows only a 3.0% reduction in variance, further strengthening the argument that students are sorted into different schools and the rural/urban/suburban nature of the school is not the primary reason for this sorting.

Grade 8 Mathematics

The modeling results are shown in Table 3. First, consistent with the Algebra I results, the student-level variables in Model 1 were all significant. The likelihood-ratio (LR) test indicates a significant improvement in the model fit between the unconditional model and Model 1 (χ^2 = 899601.5, $p < 0.0001$). The school-level variance component was dramatically reduced again (PVE=82.1%) from the null model to Model 1 with the addition of the student-level fixed effects. The PVE for the teacher-level variance was reduced 74.8%.

Research Question 2 is about whether students taught Grade 8 Mathematics out-of-field experience similar levels of academic growth as students taught in-field, as reflected in their Mathematics exam scores. The results for Model 2, which included all of the variables in Model 1 plus a teaching out-of-field variable, show that teaching out-of-field reduces student academic growth in Grade 8 Mathematics significantly (Z = -20.78, $p < 0.0001$), with test scores reduced by 15.1% of a standard deviation after accounting for the student-level variables that are correlated with test performance. The LR test indicates a significant improvement in the model fit between Model 1 and Model 2 simply by adding the teaching out-of-field variable (χ^2 = 937.5, $p < 0.0001$). After accounting for the student characteristics and teaching out-of-field, only 3.8% of the variance is left at the teacher level. The PVE between Model 1 and Model 2 for the variance at the teacher level showed it was reduced 8.1%.

The results of Model 3, which included Model 2's variables plus dummy codes for each school's locale (e.g., urban, suburban, rural), shows that teaching out-of-field was still highly significant (Z = -20.36, $p < 0.0001$) with teaching out-of-field associated with a reduction in scores equivalent to 14.9% of a standard deviation. LR test shows Model 3 resulted in a significant improvement in model fit over Model 2 (χ^2 = 44.7, p < 0.0001), but the PVE at the school level was only 0.6%.

Grade 7 Mathematics

The modeling results are shown in Table 4. First, the student-level variables in Model 1 were all significant thereby supporting their inclusion in subsequent models. The likelihood-ratio (LR) test indicates a significant improvement in the model fit between the unconditional model and Model 1 (χ^2 = 1614744.9, $p < 0.0001$). the PVE results shows the variance was reduced 88.4% at the school level and 87.6% at the teacher level.

Research Question 3 is about whether students taught Grade 7 Mathematics out-of-field experience similar levels of academic growth as students taught in-field, as reflected in their Mathematics exam scores. The results for Model 2, which included all of the variables in Model 1 plus a teaching out-of-field variable, show that teaching out-of-field reduces student academic growth in Grade 7 Mathematics significantly (Z = -9.64, $p < 0.0001$), with test scores reduced by 4.5% of a standard deviation after accounting for the student-level variables that are correlated with test performance. The LR test indicates a significant improvement in the model fit between Model 1 and Model 2 simply by adding the teaching out-of-field variable ($\chi^2 = 587.1$, $p < 0.0001$). After accounting for the student characteristics, teaching out-of-field and teacher variables, only 2.3% of the variance is left at the teacher level.

The results of Model 3, which included Model 2's variables plus dummy codes for each school's locale (e.g., urban, suburban, rural), shows that teaching out-of-field was still significant ($Z = -10.74$, $p < 0.0001$) with teaching out-of-field associated with a reduction in scores equivalent to 5.1% of a standard deviation. LR test shows Model 3 resulted in a significant improvement in model fit over Model 2 ($\chi^2 = 44.7$, p < 0.0001), but the PVE at the school level was only 0.6%.

5. Discussion

Using detailed, student-level enrollment and assessment data for 5 million unique students from Texas who completed Algebra I, Grade 8 Mathematics, or Grade 7 Mathematics between 2013 and 2019 and rigorous hierarchical linear modeling, the present study shows that students who took their Mathematics classes taught out-of-field experienced significantly and substantially less academic growth than their peers who took the same course taught in-field.

For Algebra I, students who took the course taught out-of-field earned Algebra I end-of-course (EOC) exam scores that were 11% of a standard deviation below their peers taught in-field. To put this finding into perspective, the magnitude of the negative relationship between teaching out-of-field and Algebra I test scores is 285% larger than the negative relationship between economic disadvantaged status and those test scores. In other words, putting a teacher certified to teach Algebra I into Algebra I classrooms would have almost three times the positive effect on Algebra I EOC scores as lifting students out of poverty. This pattern exists even after accounting for important differences among students, teachers, and schools.

For Grade 8 Mathematics, students who took the course taught out-of-field earned exam scores that were 15% of a standard deviation below their peers taught in-field. For Grade 7 Mathematics, students who took the course taught out-of-field earned exam scores that were 5% of a standard deviation below their peers taught in-field. These three results are important for a number of reasons.

First and foremost, students who are taught Algebra I, Grade 8 Mathematics, and Grade 7 Mathematics out-of-field experience less academic growth and therefore, are losing ground academically relative to their peers who are taught in-field. The pattern of results was consistent across all three courses. This finding is similar to several other studies (e.g., Clotfelter et al., 2010; Ingersoll, 2019; Tasi & Young, 2015), but the present results advance the field because this study combined four important characteristics. First, this study involves a direct comparison of statewide standardized exam scores between students taught in-field versus out-of-field. Second, the content covered by the exams are directly linked to the curriculum being taught in the course taught in-field or out-of-field. Third, the results are based on 1.4 to 1.8 million students in each course. Finally, the results are based on rigorous hierarchical linear modeling that address the nested structure of the data (students taught by teachers, teachers employed by schools). Clotfelter et al. (2010) came to a similar conclusion using detailed student-level data from North Carolina and comparing outcomes for students taught in-field against students taught by uncertified teachers. Tsai and Young (2015) came to a similar conclusion using international TIMSS results in science even though there was no guarantee that the science curriculum being taught was aligned directly with the exam's content. Ingersoll (2019) drew a similar conclusion using NAEP scores, and this same curricular alignment issue exists with this test.

Second, Van Overschelde and Piatt (2020) recently showed that students are not equitably enrolled in classes taught out-of-field and the inequity is growing with each passing school year since the US Congress legalized teaching out-of-field in 2015. Specifically, they found that Black students, male students, low-income students, students who are not native English speakers, students receiving special education services, and students in most locales except urban and suburban were significantly more likely to take classes taught out-of-field than their peers. Given the present study's findings, the groups of students who are taking more classes taught out-of-field are essentially receiving an inferior education – these student groups are losing ground academically relative to their White, Female, Suburban, native-English speaking, and wealthier peers.

Third, the negative relationship between teaching out-of-field and exam scores is larger in magnitude that factors like poverty and race. Given that the cost of ensuring all teachers are teaching in-field would be much lower than addressing student poverty, a federal or state policy that requires all teachers to teach in-field would dramatically improve students' learning and increase their subsequent test performance. Principals who have hiring authority over their teachers could work to ensure, to the greatest degree practicable, that all teachers are teaching in-field. This is easier said than done as principals attempt to balance budgets and teacher workloads, but larger school districts could maintain a reserve pool of teachers who can teach a class or two in each of several different schools. Any scheme to address the negative impacts of teaching out-of-field is likely to have a financial cost, but the cost of not addressing the issue is arguably much larger.

Fourth, the results strongly suggest that policymakers need to address the allocation of teachers in particular subject areas so as to create an equitable education system for all student groups. For example, the government could incentivize teachers to move to rural communities, like they have done to get teachers to teach in urban communities.

Finally, the present research shows the importance of having state longitudinal data systems (SLDS) available for researcher and for evaluating large-scale, policy-relevant educational issues. Only be collecting longitudinal data at the student-, teacher-, school-, and school district-levels is this type of research possible. An SLDS with researchers access is an important policy issue that other countries may want to consider when addressing teaching out-of-field and its impacts on students and teachers.

6. Conclusion

The legalization of teaching out-of-field since the passage of the federal Every Student Succeeds Act (2015) is negatively impacting students' academic growth and the impact is not equitable. Black students, male students, and low-income students are much more likely to take classes taught out-of-field (Van Overschelde & Piatt, 2020) and

Teaching out-of-field is an issue of equity. out-of-field teaching is bad for students. Out-of-field teaching reflects a lack of equity in the way students are educated. The removal of the federal mandates to ensure each class was taught by a highly-qualified teacher has resulted in a dramatic increase in the number of courses taught out-of-field and this change negatively impacts students of color, male students, and students in low-income families and communities. The value lost for these student groups and for society by the legalization of teaching out-of-field is substantial.

Much research has been conducted to understand the cause of teaching out-of-field. Research on why principals assign teachers to teach classes out-of-field indicates two primary reasons for this decision: 1) to save money (e.g., Bush, 2003; du Plessis, 2014; 2017; Ingersoll, 2002; Shepherd, 2013), and 2) because of a lack of sufficiently qualified teachers willing to fill a particular school's job opening (e.g., Ee-gyeong, 2011; du Plessis & Sunde, 2017; Ingersoll, 1998; Ingersoll, 2002; Ingersoll & Curran, 2004; Ingersoll et al., 2004; Jimerson, 2003; Nixon et al., 2017; Sharplin, 2014; Zhou, 2014).

With these reasons in mind, let us return to Ingersoll's analogy of cardiologists being assigned to deliver babies. Imagine a hospital administrator assigns cardiologists to deliver babies in order to either 1) save the hospital money, or 2) because an insufficient number of obstetricians are available. Would state and federal policymakers and we, as a society, treat this administrator's decision as prudent or ethical? Now, imagine that the hospital administrator makes the decision to assign obstetricians to deliver most of the White babies and cardiologists to deliver most of the babies of color? Would we believe this administrator's decision was ethical? I believe rational people would say that the administrator was acting unethically, and they might argue that the person should be arrested.

By legalizing teaching out-of-field, ESSA has resulted in the unethical and inequitable treatment of some student groups. The present findings show that the current education system in Texas violates the educational equity requirements in federal education policy for a "fair, equitable, and high-quality education" (ESSA, Sec. 1001) and the state's own education code (Texas Education Code, Sec 1.002) requirement for "equal educational services or opportunities."

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Acknowledgements

This is your acknowledgement

Table 1. Student demographic characteristics

Variable	*Algebra I*	*Grade 8 Mathematics*	*Grade 7 Mathematics*
Students	1,793,206	1,407,246	1,762,344
Teachers	20,554	14,971	16,966
Schools	3,820	2,495	2,556
Gender			
Female	900,385	691,015	876,792
Male	892,821	716,231	885,552
Ethnicity/Race			
Asian	65,207	25,897	58,657
Black/ African American	223,440	193,318	218,584
Hispanic/Latinx	935,939	784,820	949,989
Other	41,638	31,033	41,033
White	526,982	372,158	494,081
Economic Disadvantaged			
No	791,072	513,671	695,875
Yes	1,002,134	893,575	1,066,469
English Language Learner			
No	1,563,766	1,158,497	1,416,568
Yes	229,440	248,749	345,776
Special Education			
No	1,716,908	1,325,618	1,672,870
Yes	76,298	81,628	89,474
Grade Level			
Grade 8	422,860		
Grade 9	1,370,346		

Table 2. Model coefficients for Algebra I End-of-Course Exam

	Null Model Coefficient (SE)	Model 1 Coefficient (SE)	Model 2 Coefficient (SE)	Model 3 Coefficient (SE)
Level 1 (student)				
Intercept	0.135 (0.011)	-0.085 (0.005)	0.079 (0.005)	0.130 (0.005)
Female		0.053 (0.001)	0.053 (0.001)	0.053 (0.001)
Asian		0.191 (0.002)	0.191 (0.004)	0.191 (0.004)
Black		-0.024 (0.001)	-0.024 (0.002)	-0.024 (0.002)
Other		0.019 (0.003)	0.019 (0.003)	0.019 (0.003)
White		0.013 (0.001)	0.013 (0.001)	0.013 (0.001)
ELL		-0.051 (0.001)	-0.051 (0.001)	-0.051 (0.001)
SpEd		-0.170 (0.002)	-0.166 (0.002)	-0.166 (0.002)
EcoDis		-0.039 (0.001)	-0.039 (0.001)	-0.039 (0.001)
Prior Score		0.552 (0.001)	0.552 (0.001)	0.552 (0.001)
Grade 9		-0.180 (0.005)	-0.179 (0.005)	-0.177 (0.005)
SYear 2014		-0.020 (0.002)	-0.023 (0.002)	-0.023 (0.002)
SYear 2015		-0.012 (0.002)	-0.017 (0.002)	-0.017 (0.002)
SYear 2016		-0.006 (0.002)	-0.013 (0.002)	-0.013 (0.002)
SYear 2017		0.082 (0.002)	0.072 (0.002)	0.073 (0.002)
SYear 2018		-0.009 (0.002)	-0.002 (0.002)	-0.002 (0.002)
SYear 2019		-0.004 (0.002)	-0.010 (0.003)	-0.010 (0.003)
Level 2 (teacher)				
TOOF (random)			**-0.111 (0.006)**	**-0.104 (0.006)**
Teaching Experience			0.003 (0.000)	0.003 (0.000)

No Degree			-0.026 (0.007)	-0.025 (0.010)
Masters			-0.005 (0.003)	-0.004 (0.003)
Doctorate			-0.086 (0.018)	-0.085 (0.018)
Level 3 (school)				
Urban				-0.015 (0.014)
Central				-0.029 (0.013)
Central Suburban				-0.090 (0.012)
Independent				-0.084 (0.017)
Fast Growing				-0.062 (0.017)
Stable				-0.080 (0.013)
Rural				-0.068 (0.013)
Charter				-0.116 (0.015)
Level 1 variance (student)	0.470 (0.000)	0.275 (0.002)	0.275 (0.000)	0.275 (0.000)
Level 2 variance (teacher)	0.111 (0.002)	0.040 (0.001)	0.037 (0.001)	0.037 (0.001)
TOOF			0.025 (0.002)	0.025 (0.002)
Level 3 variance (school)	0.397 (0.011)	0.044 (0.002)	0.042 (0.002)	0.041 (0.001)
χ^2 for model improvement		971733.0	1264.9	126.5

Note: SpEd = special education, ELL = English language learner, EcoDis = Economically disadvantaged, SYear = school year where the digits represent the year of the spring semester (e.g., SYear2017 = school year 2016-2017), $^{\#}p > 0.10$, $^{*}p < 0.10$, $^{***}p < 0.01$. If coefficient not marked, then $p < 0.0001$.

Table 3. Model coefficients for Grade 8 Mathematics

	Null Model Coefficient (SE)	Model 1 Coefficient (SE)	Model 2 Coefficient (SE)	Model 3 Coefficient (SE)
Level 1 (student)				
Intercept	-0.278 (0.008)	0.070 (0.004)	0.073 (0.005)	0.092 (0.008)
Female		0.065 (0.001)	0.065 (0.001)	0.065 (0.001)
Asian		0.174 (0.004)	0.174 (0.004)	0.174 (0.004)
Black		-0.046 (0.002)	-0.046 (0.002)	-0.046 (0.002)
Other		0.016 (0.003)	0.016 (0.003)	0.016 (0.003)
White		0.014 (0.001)	0.014 (0.001)	0.014 (0.001)
ELL		-0.045 (0.001)	-0.045 (0.001)	-0.045 (0.001)
SpEd		-0.241 (0.002)	-0.237 (0.002)	-0.237 (0.002)
EcoDis		-0.043 (0.001)	-0.043 (0.001)	-0.043 (0.001)
Prior Score		0.756 (0.001)	0.756 (0.001)	0.756 (0.001)
SYear 2014		-0.080 (0.002)	-0.083 (0.002)	-0.083 (0.002)
SYear 2015		-0.055 (0.002)	-0.062 (0.002)	-0.061 (0.002)
SYear 2016		-0.051 (0.002)	-0.060 (0.002)	-0.059 (0.002)
SYear 2017		0.053 (0.002)	0.041 (0.002)	0.041 (0.002)
SYear 2018		-0.023 (0.002)	-0.036 (0.002)	-0.036 (0.002)
SYear 2019		-0.037 (0.003)	-0.053 (0.003)	-0.054 (0.003)
Level 2 (teacher)				
TOOF (random)			**-0.151 (0.009)**	**-0.149 (0.009)**
Teaching Experience			0.003 (0.000)	0.003 (0.000)
No Degree			-0.085 (0.010)	-0.084 (0.010)

Masters			-0.006 (0.004)	-0.006 (0.004)
Doctorate			-0.001 (0.022)	-0.000 (0.022)
Level 3 (school)				
Urban				-0.021 (0.012)
Central				-0.046 (0.012)
Central Suburban				-0.012 (0.012)
Independent				-0.051 (0.017)
Fast Growing				-0.015 (0.018)
Stable				-0.015 (0.013)
Rural				-0.027 (0.011)
Charter				-0.033 (0.014)
Level 1 variance (student)	0.606 (0.001)	0.322 (0.000)	0.322 (0.000)	0.275 (0.000)
Level 2 variance (teacher)	0.165 (0.003)	0.041 (0.001)	0.038 (0.001)	0.037 (0.001)
TOOF			0.026 (0.003)	0.025 (0.002)
Level 3 variance (school)	0.111 (0.005)	0.020 (0.000)	0.019 (0.001)	0.041 (0.001)
χ^2 for model improvement		899601.5	1160.95	126.5

Note: SpEd = special education, ELL = English language learner, EcoDis = Economically disadvantaged, SYear = school year where the digits represent the year of the spring semester (e.g., SYear2017 = school year 2016-2017), $^{\#}p > 0.10$, $^{*}p < 0.10$, $^{***}p < 0.01$. If coefficient not marked, then $p < 0.0001$.

Table 4. Model coefficients for Grade 7 Mathematics

	Null Model Coefficient (SE)	Model 1 Coefficient (SE)	Model 2 Coefficient (SE)	Model 3 Coefficient (SE)
Level 1 (student)				
Intercept	-0.169 (0.008)	0.052 (0.003)	0.046 (0.003)	0.047 (0.007)
Predictors				
Female		0.031 (0.001)	0.031 (0.001)	0.031 (0.001)
Asian		0.198 (0.002)	0.198 (0.002)	0.198 (0.002)
Black		-0.063 (0.001)	-0.063 (0.001)	-0.063 (0.001)
Other		0.016 (0.003)	0.016 (0.003)	0.016 (0.003)
White		0.026 (0.001)	0.026 (0.001)	0.026 (0.001)
ELL		-0.053 (0.001)	-0.053 (0.001)	-0.053 (0.001)
SpEd		-0.154 (0.002)	-0.153 (0.002)	-0.152 (0.002)
EcoDis		-0.063 (0.001)	-0.063 (0.001)	-0.063 (0.001)
Prior Score		0.775 (0.001)	0.775 (0.001)	0.775 (0.001)
SYear 2014		-0.014 (0.002)	-0.016 (0.002)	-0.017 (0.002)
SYear 2015		-0.006 (0.002)	-0.011 (0.002)	-0.011 (0.002)
SYear 2016		0.003 (0.002)	0.004 (0.002)	0.005 (0.002)
SYear 2017		0.079 (0.002)	0.070 (0.002)	0.069 (0.002)
SYear 2018		0.049 (0.002)	0.038 (0.002)	0.037 (0.002)
SYear 2019		0.059 (0.002)	0.046 (0.002)	0.044 (0.002)
Level 2 (teacher)				
TOOF (random)			**-0.045 (0.005)**	**-0.051 (0.005)**
Teaching Experience			0.003 (0.000)	0.003 (0.000)

No Degree			-0.033 (0.007)	-0.033 (0.007)
Masters			-0.002 (0.003)	-0.002 (0.003)
Doctorate			-0.026 (0.020)	-0.030 (0.020)
Level 3 (school)				
Urban				-0.025 (0.010)
Central				-0.033 (0.010)
Central Suburban				-0.002 (0.010)
Independent				-0.011 (0.015)
Fast Growing				-0.013 (0.015)
Stable				-0.012 (0.011)
Rural				-0.007 (0.009)
Charter				-0.069 (0.010)
Level 1 variance (student)	0.663 (0.001)	0.268 (0.001)	0.268 (0.001)	0.268 (0.001)
Level 2 variance (teacher)	0.194 (0.003)	0.023 (0.000)	0.023 (0.000)	0.023 (0.000)
TOOF			0.012 (0.001)	0.012 (0.001)
Level 3 variance (school)	0.122 (0.005)	0.014 (0.000)	0.014 (0.000)	0.014 (0.000)
χ^2 for model improvement		1614744.9	587.1	103.9

Note: The predictor variables are fixed effects, except where noted. TOOF = Teaching out-of-field, SpEd = special education, ELL = English language learner, EcoDis = Economically disadvantaged, SYear = school year where the digits represent the year of the spring semester (e.g., SYear2017 = school year 2016-2017), $^{\#}p > 0.10$, $^{@}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. If coefficient not marked, then $p < 0.0001$.